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published in
Transportation Research Record
2019

DOI (link to publisher)
10.1177/0361198119837495

citation for published version (APA)
Waterbolk, M., Tump, J., Klaver, R., van der Woude, R., Velleman, D., Zuidema, J., Koch, T., & Dugundji, E. (2019). Detection of Ships at Mooring Dolphins with Hidden Markov Models. *Transportation Research Record*, *2673*(4), 439-447. https://doi.org/10.1177/0361198119837495

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Freight

Transportation Research Record
2019, Vol. 2673(4) 439–447

DOI: 10.1177/0361198119837495
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Detection of Ships at Mooring Dolphins with Hidden Markov Models

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Abstract

IJpalen near the lock in IJmuiden are of great economic value to the Port of Amsterdam. These mooring dolphins have to endure a considerable amount of kinetic forces which can have an impact on the condition of the dolphins. These forces are created by either mooring or already moored ships. Any irregularities taking place at the IJpalen can have disastrous results unless timely addressed. The Port of Amsterdam has attached sensors to the poles and the plates, which measure changes in the dimensions regarding the dolphins. This report explores whether combining sensor data from the IJpalen and automatic identification system (AIS) data can produce beneficial insights into the dolphins' states. We have used the sensor dataset to build a hidden Markov model (HMM) which predicts whether a ship is moored. We evaluated these results using the AIS data, in which can be discovered when a ship was moored at the IJpalen, producing remarkable results. We analyzed the sensor values using descriptive statistics to discover the normal and problem values. This research has obtained the following findings. First, descriptive statistics indicate a normal value range for the sensor values. Whenever a value out of this range is observed, it could be a problem case. Finally, it is possible to detect whether a ship is moored in the sensor data. An HMM on the z-angle of the plate of the east dolphin produces the best prediction, i.e., the highest accuracy of 90.2% according to the evaluation method, of a moored ship at the IJpalen.

The Port of Amsterdam is one of Europe's biggest ports and "plays a large role in the transshipment and processing of energy products" (*1*, *2*). Every year 95 million tons of cargo are transshipped through the port by over 7000 sea vessels and 40,000 barges. Altogether, the Port of Amsterdam provides 55,000 jobs and is the world's largest gasoline harbor (*3*, *4*). Because the Port of Amsterdam's greatest source of income is the import of fossil fuels, which is declining, it is of great importance that the port innovates to compensate for the losses (*5*). The port innovates by digitizing many different aspects within the port. One example is the use of drones, which the port uses to inspect ships. Another way of innovation is using sensors at the IJpalen.

The IJpalen are two mooring dolphins just outside the western lock of the port. To enter the Port of Amsterdam, ships are required to pass through this lock, the Noordzeesluis, at IJmuiden. Ships that have a draught of more than 13.75 m have to transfer part of their cargo into barges, at the IJpalen, to reduce their draught to pass the lock safely (*6*).

These dolphins are of great economic value to the Port of Amsterdam as they allow ships that lie too deep to deliver their goods. These ships typically carry a larger load, i.e., a larger economical value, than the ships that can go through the lock without having to transfer cargo. If ships are unable to moor to these posts because of bad conditions, the Port of Amsterdam is likely to lose significant income. Therefore, it is important that the IJpalen are in good condition.

The IJpalen have to endure a considerable amount of kinetic forces which can have an impact on the condition of the dolphins. These forces are created by either mooring or already moored ships. It has been demonstrated that "a moored ship manifests surge, sway, heave, roll, pitch and yaw motions under the action of wave, wind and current", which can result in damage to the dolphins (*7*). The dolphins each have a cone fender to absorb these

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forces, and a plate to which the boats moor. The port has attached sensors to the pole and the plate, which measure changes in the dimensions regarding the dolphins, such as the angle of the plate and pole and the distance between them. The port would like to use the sensors to detect whether a ship is moored and if there are problems with the IJpalen; abnormal sensor values indicate these problems.

However, the Port of Amsterdam currently does not use the data from the sensors because the port does not have the expertise to extract this information from the sensor data. At the moment, the port could also use the AIS data, which is GPS, static, and dynamic information transmitted by ships, to determine if a ship is moored at the IJpalen. This might not be possible in the future because of the General Data Protection Regulation (GDPR) in Europe. Hence, our goal is to construct a model which determines whether a ship is moored using only the sensor data, and to detect problem cases.

Problem Description

The IJpalen are two mooring dolphins: the east and west dolphin. (Figure 1) shows the location of the IJpalen. The two red dots represent the dolphins and the yellow and blue dots are receivers for the data sent by the sensors of the dolphins. The ships come from the sea on the left side of the figure and go through the lock on the right side to access the Port of Amsterdam.

When a ship has a draught over 13.75 m it cannot pass through the lock (*6*). The ship then needs to moor at the IJpalen to transfer part of its cargo into barges to reduce its draught. Pilot ships assist these ships during the mooring process by hauling them against the dolphins. This is done with high caution to avoid rough collision with the dolphins, because this could lead to damage. Moreover, when a ship is moored incorrectly, it can result in unpredictable movement of the ship. These movements are caused by, for example, suction created by passing ships, which could also lead to damage of the dolphins. After part of the cargo is transferred, the ship can pass the Noordzeesluis and continue its journey to the port.

Figure 1. Location of the IJpalen mooring dolphins.

As mentioned in the introduction the IJpalen are of great significance for the port. If the dolphins are out of service because of damage, it will result in the following costs. First, the port would have to pay €200,000 for a new pole plus the costs of the replacing process. Second, the port would lose out on revenue as it temporarily cannot serve overloaded ships, which as a result would have to deviate to the Port of Rotterdam or Antwerp. Most importantly, however, the port would suffer long term reputational damage since the port becomes unreliable and this could lead to the ships permanently using the Port of Rotterdam or Antwerp instead of the Port of Amsterdam (*3*).

Currently, employees of the port inspect the exterior of the dolphins at least three times a year. Employees perform additional inspections when the company Koperen Ploeg, which moors ships at the IJpalen, reports that something might be wrong with the dolphins (*3*). However, these inspections are not sufficient. The inspectors, for example, cannot observe slight modifications in the angle of the dolphins which could lead to damage.

To be able to inspect these modifications, the Port of Amsterdam has had sensors placed on the dolphins. The port can monitor the angles of the pole and plate of the dolphins with these sensors, e.g., to find out if the dolphins are out of plumb. However, at the moment the port only uses a dashboard to monitor the angles. Not much information about irregularities in the angles, possible problem cases, can be gained from this dashboard, as the port does not know what the normal values of the sensors are. Moreover, the port does not know when a ship is moored. This can currently be extracted from the AIS data but because of the GDPR this might not be possible in the future. Therefore, we also need to detect if a ship is moored from the sensor data.

The Port of Amsterdam has asked us to compare the sensor data with AIS data, to see if valuable information can be obtained from this comparison. The port has also asked us to investigate the following sub-problems:

- Is it possible to detect in both datasets when a ship is moored?
- What values do the sensors show when a ship moors?
- What is a normal mooring situation? Can we isolate problem cases?
- How reliable are the values from the sensors?

Data Description

In this section we outline the different datasets that were used. First, we describe the automatic identification system (AIS) data. Following that, we explain the sensor data.

Automatic Identification System

The AIS is an automatic tracking system of sea vessels, which is mandatory for "all commercial vessels over 299 gross tonnage (GT) that travel internationally" (*8*). The AIS has been introduced to provide more safety at sea and inland water. It provides a captain with more information than a traditional radar would, for example the heading of other vessels. The AIS uses very high frequency (VHF) to transmit information between vessels and the quay. The AIS data of a vessel is transmitted every two to ten seconds while sailing depending on the vessel's speed. When the vessel is anchored, the data is transmitted every three minutes. The AIS transmits a total of twenty variables and makes a distinction between static and dynamic information (*9*).

The crew provides the static information, however, not all of these variables are accurate or filled in. This information is broadcast every three minutes and consists of ten variables. The dataset that will be investigated contains the following nine static variables: international maritime organization (IMO) number, call sign, ship name, ship type, ship dimensions, position of the antenna on the vessel, draught, destination, and estimated time of arrival (ETA).

The ship itself produces the dynamic information using its own gyrocompass and global navigation satellite system (GNSS). The dynamic information variables in the dataset are the following: maritime mobile service identity (MMSI) number, AIS navigational status, rate of turn, speed over ground, position coordinates (latitude/longitude), course over ground, heading, bearing at own position, and UTC seconds.

The AIS dataset contains time stamps of when the AIS broadcast was received. However, some of these time stamps had to be input because of an error in the receiver. Therefore, some of the time stamps can be unreliable.

Sensor Data

Each dolphin has a range of sensors attached to it. A dolphin exists of a pole, a cone fender, and a plate. The port has attached sensors to both the pole and the plate. The pole sensors measure the x-angle and z-angle of the pole and the plate sensors measure the x-angle and z-angle of the plate. Furthermore, the sensors measure distance between the plate and pole by measuring the distance between both sensors. This distance indicates how much the cone fender is indented. Figure 2 shows a three-dimensional representation of a dolphin. In addition to the two dolphins, the Port of Amsterdam placed a third pole next to the IJpalen for transmitting the signal of the sensors to the receiver on the tower, the Nederlandse Loodswezen (*3*). The port placed this additional pole because otherwise moored vessels would block the signal from the IJpalen to the tower.

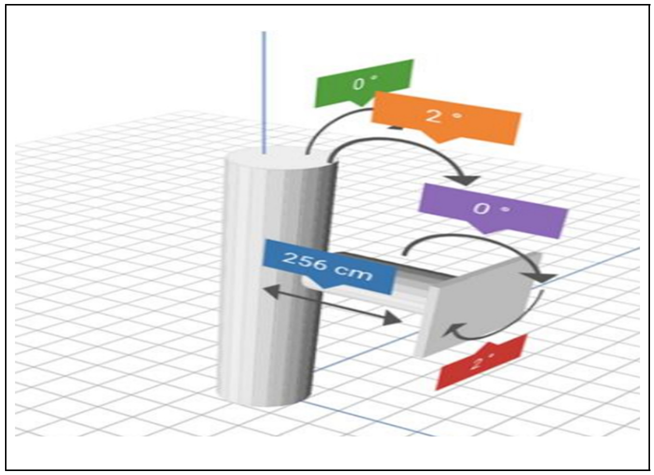

Figure 2. A three-dimensional representation of a dolphin, with sensors. (*10*).

Methodology

This section starts by explaining the processing of the AIS data and the sensor data. Next, we describe the hidden Markov model (HMM). Finally, we explain the evaluation method, a strategy to evaluate the accurateness of the HMM using the AIS data.

AIS Data

As mentioned in the data description, an AIS broadcast contains a plethora of data. In the scope of detecting whether a ship is moored at the IJpalen or not, a number of variables are useful. These variables are the latitude and longitude, the heading, the dimensions, and the time stamps. We have taken the following steps for both dolphins to detect if a ship has come into contact with them.

First, we compared the heading of the ship to the heading it should have, to be able to come into contact with the dolphin. If these angles are not alike, the ship cannot be in contact with the dolphin. Second, if the angles do match, we compared the ship's dimensions with the distance of the ship to the dolphin. If the ship is physically able to touch the dolphin, then we can conclude that the ship has come into contact with the dolphin.

The time stamps, which can be converted into date and time, are used to detect when a ship is moored or mooring. When a ship has made contact with one of the dolphins, the ship has started mooring. Then, we compare the time between the consecutive time stamps. When the ship is moored, it only sends out an AIS signal every three minutes. If the difference is one minute, the ship is still mooring. As a result, a value can be linked to every time stamp for each ship: 0 if the ship is not in contact with one of the dolphins, 1 if the ship is mooring, and 2 if the ship is moored at the IJpalen.

The AIS data showed one anomaly on the 17th of November. On this day, no time stamps were recorded. The ship *Anangel Spirit* is deleted from the dataset as the ship arrived on this day. Therefore, the moment of mooring cannot be deduced.

Sensor Data

The sensors provide nine datasets which each represent a month worth of sensor data. First, we have split each dataset in six datasets, representing the six different sensor variables. Each of these new datasets consists of the time stamps combined with either: the angles of the west pole; the angles of the east pole; the angles of the west plate; the angles of the east plate; the distances of the west pole; or the distances of the east pole. Next, we have combined all months of datasets corresponding to the same sensor variable to create datasets that represent the data from August 2017 until April 2018.

Some of these datasets were incomplete. First, each dataset contains some missing values because they are not filled in. We have set these values to zero, in agreement with the Port of Amsterdam. Second, we have deleted a period in October from all datasets since these values were not accurate because of a malfunction. Finally, we have deleted some months at the end of some datasets, because they solely contained missing values. This was because of battery issues in some of the sensors. A few datasets only have valuable information until January whereas others have valuable information until April. Hence, all datasets have different lengths.

Furthermore, we have sorted the data by date and aggregated to intervals of 1, 6, 15, 30 and 60 minutes. We have done the aggregation by calculating the average of the sensor variable from the values it spans for each interval.

Hidden Markov Model

The HMM is a probabilistic sequence model which was originally proposed by Baum (*11*). It assumes that the observed data is generated by a Markov process, which is “a stochastic model describing a sequence of possible events in which the probability of each event depends only on the state attained in the previous event” (*12*).

Contrary to a Markov model, the observations are a probabilistic function of the states and this underlying state sequence itself is a hidden stochastic process (*13*).

HMMs have proven themselves as being very reliable in detecting whether data originates from a different state in speech recognition and biological sequences (*14*). An HMM is defined as

$Q = q_1, q_2, \ldots, q_N$	*a set of N states*
$A = a_{11}, a_{12}, \ldots, a_{n1}, \ldots, a_{nn}$	*a transition matrix A, each a_{ij} representing the probability of moving from state i to state j s.t* $\sum_{j=1}^{n} a_{ij} 1, i = 1, \ldots, n$
$O = o_1, o_2, \ldots, o_T$	*a sequence of T observations*
$B = b_i(o_t)$	*a sequence of observation likelihoods, also called emission probabilities, each expressing the probability of an observationo_t being generated from a state i*
$\Pi = \{\pi_1, \pi_2, \ldots, \pi_N\}$	*an initial probability distribution over states. Π_i is the probability that the Markov chain will start in state i*
$S = s_1, s_2, \ldots, s_T$	*hidden state sequence*

With this definition (*15*), we can construct an HMM. A graphical representation of the HMM used for this research is shown in (Figure 3).

Using the HMM which we will call λ, which is set with values for *A* and *B* to get λ = (*A,B*), the following questions can be answered (*15*):

1. Given an HMM λ and an observations sequence *O*, what is the likelihood *P*(*O*|λ)?
2. Given an observation sequence *O* and an HMM λ, what is the best hidden state sequence *Q*?
3. Given an observation sequence *O* and the set of states in the HMM, what are the HMM parameters of *A* and *B*?

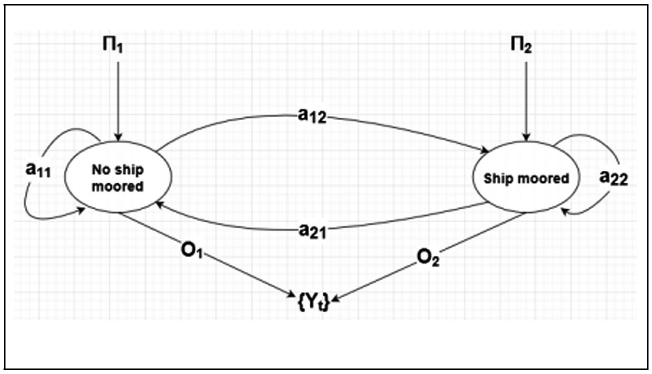

Figure 3. An HMM for relating the value of Yt to a ship being moored or no ship moored.

In scientific literature these three questions are referred to as "the fundamental problems of HMM" (*15*). To answer these questions, we first have to derive $P(O|\lambda)$. This can be calculated by solving

$$P(O|\lambda) = \sum_{S} \pi_{s1} \prod_{t=2}^{T} a_{s_{t-1}s_t} \prod_{t=1}^{T} b_{st}(o_t)$$

Normally, this equation is solved by computing a separate observation likelihood for each hidden state sequence and then summing them. Since for an HMM with N hidden states and an observation sequence of T observations, there are $N\ T$ possible hidden sequences. To circumvent this issue, we use the forward algorithm.

In this research we have assumed that $bi(ot)$ is following a multivariate Gaussian distribution.

We answer the second question, also known as the decoding problem, using the Viterbi algorithm. The Viterbi algorithm is used to determine which sequence of variables is the underlying source of some sequence of observations. Because of the exponential amount of combination of sequences, the Viterbi algorithm is used to efficiently calculate this. The algorithm returns the most likely state sequence based on the maximum likelihood of the observation sequence. Note that the Viterbi algorithm is almost identical to the forward algorithm except that it takes the maximum over the sequence probabilities whereas the forward algorithm takes the sum (*15*).

We answer the third question, also known as the learning problem, using the expectation–maximization algorithm (*13*). The algorithm will let us train both the transition probabilities A and the emission probabilities B of the HMM. It works by first computing an initial estimate for the probabilities, then with these estimates iteratively computing a better estimate (*15*).

We will use the HMM for this particular case in the following way. First, we will answer the third question. Then, with this estimated λ, we can answer the second question and give a prediction.

Evaluation Method

We have created an evaluation method to test the performance of the HMM. This method calculates the accuracy of the HMM, where a high accuracy indicates that the HMM performs well, whereas a low accuracy means the HMM does not perform well.

The vector created from the AIS data, indicating whether there is no ship or a ship is moored, is compared with a prediction vector created by the HMM. This prediction is a vector containing zeros and ones. Where value one indicates the model predicts that there is a ship at the IJpalen, and value zero indicates the model predicts that there is no ship moored. A resulting vector is constructed by subtracting the actual vector of the AIS data by the HMM vector. The formula used is

$$Resulting\ vecor = AIS\ vector - HMM\ vector$$

The resulting vector consists of zeros, ones, and minus ones. A value of zero means the HMM correctly predicted whether a ship was moored or not.

A value of one means the HMM failed to predict that a ship was moored, i.e., the AIS shows that a ship was moored, but the HMM has predicted no ship was moored. A value of minus one indicates that the HMM failed to predict that no ship was moored, i.e., according to the AIS no ship was moored, but the HMM doesn't predict so.

Finally, we calculated the accuracy by calculating the percentage of correctly predicted observations (the zeros in the resulting vector). The formula is

$$Forecast\ accuracy = \frac{Correctly\ predicted\ observations}{Total\ observations} * 100\%$$

Results

In this section we show the results of the implemented methods. First, we present the results of detecting if a ship is moored in the AIS data and the results of analyzing the sensor data. Second, we show the results of the evaluation method on the HMM.

Resulting AIS Data

We have used the AIS data to deduce the situation at the IJpalen. We have recognized the following situations in the data: no ship, ship mooring, and ship moored at the dolphins. The results are shown in Table 1. On average, the ships take about half an hour to moor. Most of the time, a ship stays for just one or a couple of days. However, sometimes ships do stay longer, for example the *Hubert Fedry* stayed for six days.

Table 1. Overview of the Situations at the IJpalen between November 2017 and the Start of February 2018

Ship	Start mooring	Moored	Leaving
Lowlands Comfor	02/02/2018 8:29	02/02/2018 9:11	03/02/2018 7:26
Andromeda Ocean	01/02/2018 14:31	01/02/2018 14:47	01/02/2018 21:59
Gotia	29/01/2018 18:22	29/01/2018 18:37	01/02/2018 7:56
Attikos	24/01/2018 0:59	24/01/2018 1:25	26/01/2018 21:59
Ocean Ambition	15/01/2018 6:28	15/01/2018 6:45	16/01/2018 5:38
Jin Tai Feng	09/01/2018 0:39	09/01/2018 1:00	09/01/2018 9:00
Golden Arion	08/01/2018 7:46	08/01/2018 8:05	08/01/2018 22:20
Grand Marcia	05/01/2018 10:13	05/01/2018 10:31	05/01/2018 22:01
Hubert Fedry	22/12/2017 22:42	22/12/2017 23:06	28/12/2017 10:36
Hispanic G	21/12/2017 8:54	21/12/2017 9:16	22/12/2017 8:29
He Hua Hai	11/12/2017 19:53	11/12/2017 20:16	12/12/2017 11:41
GL Colmena	05/12/2017 8:01	05/12/2017 8:22	05/12/2017 19:36
SBI Parapara	04/12/2017 6:33	04/12/2017 7:07	04/12/2017 21:27
Shandong Fu Ze	28/11/2017 13:41	28/11/2017 14:01	29/11/2017 4:22
Navios Sphera	27/11/2017 6:15	27/11/2017 6:37	28/11/2017 8:37
FD Angelica	24/11/2017 11:35	24/11/2017 11:56	24/11/2017 18:23
Hero	21/11/2017 9:30	21/11/2017 9:50	24/11/2017 10:30
GL Colmena	15/11/2017 17:36	15/11/2017 17:52	16/11/2017 0:47
Junior	09/11/2017 17:01	09/11/2017 17:21	10/11/2017 7:04

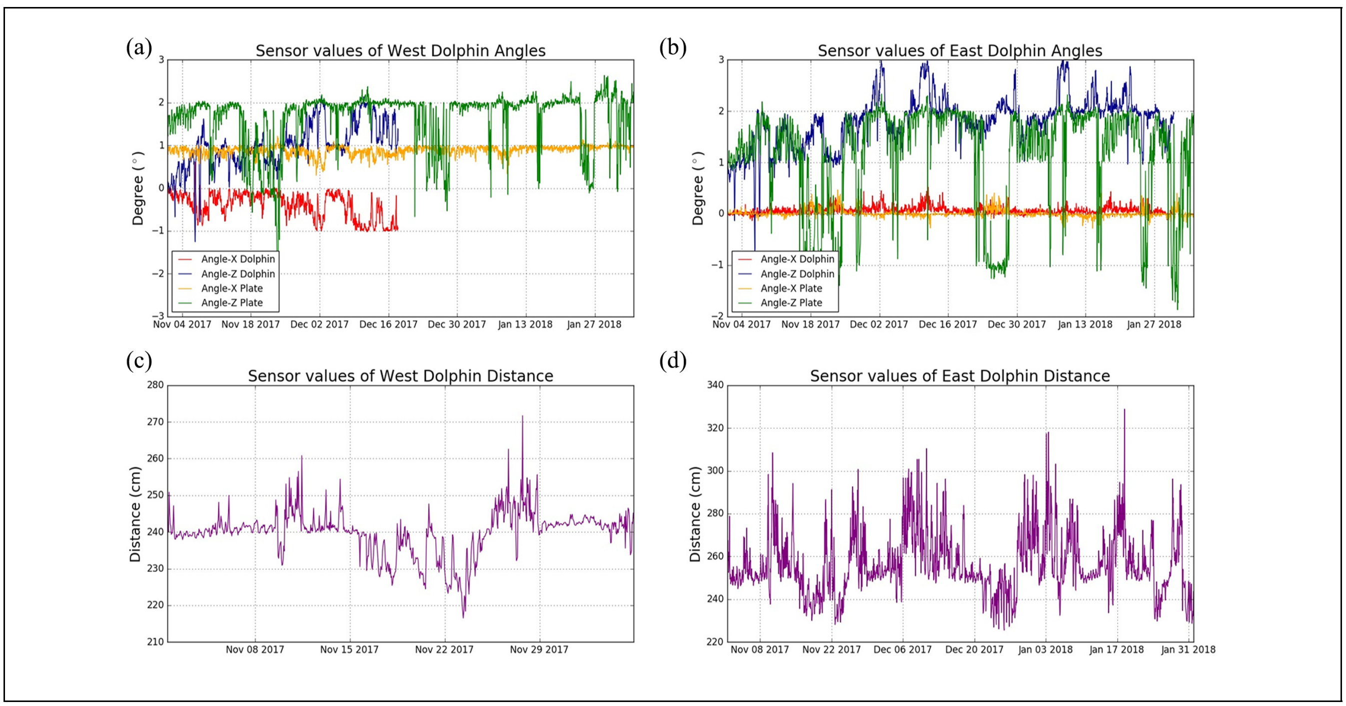

Figure 4. Overview of the final dataset aggregated by hour: (*a*) west dolphin angles, (*b*) east dolphin angles, (*c*) west dolphin distances, (*d*) east dolphin distances.

Resulting Sensor Data

The sensor data after processing, i.e., aggregating, are shown in Figure 4. The angle data of the west pole and both distance datasets span a smaller time frame than the other sensor variables, as can be seen in the figure. All datasets have a high rate of fluctuation and all have a different means. The next two sections will delve deeper into the analysis of these values.

Hidden Markov Model

We have used an HMM to determine whether a ship is moored or not, according to the sensor data. In Table 2,

Table 2. HMM Forecasts for Data Aggregated into Averages for Indicated Sensor Data

	Score 6 min	Score 15 min	Score 30 min	Score 60 min
East dolphin *z*-angle plate	0.902	0.905	0.907	0.908
East dolphin *x*-angle plate	0.250	0.246	0.201	0.201
East dolphin *x*-angle	0.423	0.683	0.699	0.694
East dolphin *z*-angle	0.617	0.615	0.615	0.621
East dolphin distance	0.461	0.424	0.430	0.430
West dolphin *z*-angle plate	0.842	0.838	0.829	0.833
West dolphin *x*-angle plate	0.501	0.471	0.495	0.506
West dolphin *x*-angle	0.498	0.446	0.420	0.406
West dolphin *z*-angle	0.567	0.571	0.560	0.559
West dolphin distance	0.198	0.204	0.191	0.152

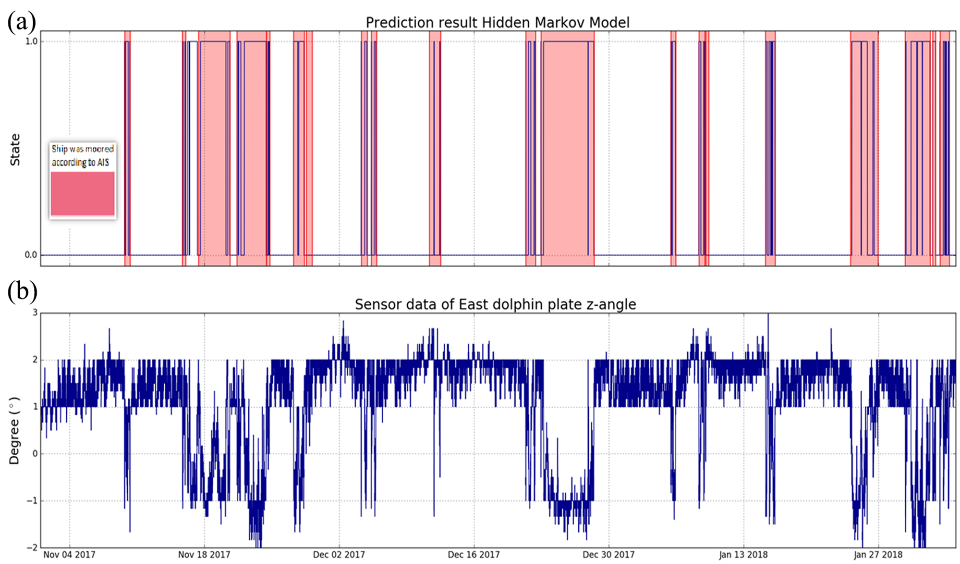

Figure 5. Prediction east plate *z*-angle: (*a*) HMM prediction result, (*b*) the sensor data which the model uses.

the forecast accuracies for the sensors are shown. The higher the forecast accuracy, the better the prediction. The number of minutes indicates the aggregation method used.

The table shows there is a high contrast between the performance of each sensor; some are very high while others have a very low forecast accuracy.

The best performing model is the model constructed with the east dolphin *z*-angle plate 60-min data (Table 2). This model has a prediction rate of 90.8%. Hence, the values of the *z*-angle of the plates indicate a difference between the situation of no ship moored and a ship moored. Since this is based on hourly data, this result might not be interesting for the Port of Amsterdam, as they might want to be able to predict the situation more real-time. However, the 6-min raw data has a similar prediction rate of 90.2% (Table 2), thus this data is most suitable for the HMM for the port to use.

Figure 5 shows the results for the HMM on a 6-min basis. The pink area indicates that a ship was moored at that time according to the AIS data. State 1 indicates that the HMM predicts that a ship was moored and state 0 indicates that no ship was moored according to the HMM. The prediction rate for the 6-min data is 90.2%.

Figure 5*b* shows a clear change in the sensor data when a state change occurs. When a ship is moored, the values tend to be lower. The mean for the state that a ship was moored is −0.661 and the variance is 0.3639. The mean for the state when there is no ship moored is 1.6137 and the variance is 0.1601.

The following two tables (Tables 3 and 4) show an overview of the boundary values for each sensor variable

Table 3. West Dolphin Boundary Values

Sensor west dolphin	No ship	Ship moored
Pole x-angle	[−2,1]	[0]
Pole z-angle	[1]	[1]
Plate x-angle	[1]	[1]
Plate z-angle	[2]	[−3,4]
Distance	[235, 246]	[212, 260]

Table 4. East Dolphin Boundary Values

Sensor east dolphin	No ship	Ship moored
Pole x-angle	[0]	[0]
Pole z-angle	[0,3]	[0,3]
Plate x-angle	[0]	[0]
Plate z-angle	[0,3]	[−2,3]
Distance	[235,270]	[209, 289]

based on the 6-min sensor data. It is easy to see that there is not much variability in the boundary values of the west dolphin: z-angle, x-angle, plate x-angle and the east dolphin: x-angle, z-angle, plate x-angle. This can explain why the HMM performed worse on these datasets than on the datasets that show more variability. By knowing what states the IJpalen are in, we can deem values normal or abnormal. An abnormal value is an observed value outside the intervals. If the port observes multiple abnormal values subsequently, there might be a problem at the IJpalen.

Conclusion

Analysis of the sensor data and AIS data revealed it is possible to detect from both datasets whether a ship is moored. The analysis shows that there is a significant difference between some sensor values when a ship is moored and when there is no ship moored.

The analysis shows that the z-angle of the east and west dolphin plate are the sensor variables which show a difference between the situation of no ship moored and a ship moored. When a value below 0° is observed at the east dolphin we can conclude that a ship is moored. When a value other than 2° is observed at the west dolphin we can conclude that a ship is moored. Furthermore, by knowing what state the IJpalen are in, we can deem the sensor values at that moment normal or abnormal. Multiple abnormal values observed subsequently indicate problem cases.

For the following variables, most observed values of the different states are equal to each other: east dolphin x-angle, east dolphin z-angle, west dolphin z-angle, west dolphin x-angle, west and east dolphin plate x-angle. This results in a high level of ambiguity to determine whether a ship is moored or not and can explain why the HMM performed badly on these datasets. Thus, we would recommend not to use these sensor variables.

According to the evaluation method, the best-performing HMM is based on 6-min east dolphin z-angle plate and has a prediction accuracy of 90.2%. This indicates the sensor data is reliable for the Port of Amsterdam to use as a detection system of whether a ship is moored and to detect problem cases. The mean for the state that a ship is moored is −0.661 and the variance is 0.3639; the mean for the state when there is no ship moored is 1.6137 and the variance is 0.1601. Since the east and west dolphin z-angle plate have the highest prediction rates, we deem these datasets to be the most reliable for determining whether a ship is moored or not.

By combining the HMM results with the descriptive analysis we can investigate the normality of the current sensor values. We can determine if a ship is moored using the best-performing HMM and whether the observed values are abnormal. Hence, with this research, we have provided the Port of Amsterdam with a method to obtain insightful information from the sensor data.

Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: MW, JT, JZ, ED; data collection: JT, DV, JZ, TK; analysis and interpretation of results: MW, RW, RK; draft manuscript preparation: MW, RW, RK, ED. All authors reviewed the results and approved the final version of the manuscript.

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The Standing Committee on Ports and Channels (AW010) peer-reviewed this paper (19-02045).